Market manipulation and suspicious stock recommendations on social media

Thomas Renault*[a,b]

[a]Université Paris 1 Panthéon Sorbonne, Paris, France

Abstract

Social media can help investors gather and share information about stock markets. However, it also presents opportunities for fraudsters to spread false or misleading statements in the marketplace. Analyzing millions of messages sent on the social media platform Twitter about small capitalization firms, we find that an abnormally high number of messages on social media is associated with a large price increase on the event day and followed by a sharp price reversal over the next trading week. Examining users' characteristics, and controlling for lagged abnormal returns, press releases, tweets sentiment and firms' characteristics, we find that the price reversal pattern is stronger when the events are generated by the tweeting activity of stock promoters or by the tweeting activity of accounts dedicated to tracking pump-and-dump schemes. Overall, our findings are consistent with the patterns of a pump-and-dump scheme, where fraudsters/promoters use social media to temporarily inflate the price of small capitalization stocks.

Keywords: Asset Pricing, Market efficiency, Market manipulation, Pump-and-dump scheme, Stock promotion, Small capitalization stocks, Social media, Twitter, Event study, Security and Exchange Commission

JEL classification: G12, G14.

*Electronic address: thomas.renault@univ-paris1.fr; Corresponding author: Thomas Renault. Maison des Sciences conomiques - 106-112 bd de l'Hpital, 75642 Paris Cedex 13

1. Introduction

Market manipulation is as old as trading on organized exchanges (Putniņš, 2012). However, despite their long prevalance and considerable academic research on the topic, our understanding of the phenomenon is far from adequate. While theoretical models have been developed to address trade-based manipulation (Allen and Gale, 1992) or information-based manipulation (Bommel, 2003), empirical studies continue to be very scarce. This paper contributes to the emerging empirical literature on market manipulation by focusing on a specific type of illegal price manipulation: pump-and-dump schemes.

Pump-and-dump schemes involve touting a company's stock through false or misleading statements in the marketplace in order to artificially inflate (pump) the price of a stock. Once fraudsters stop hyping the stock and sell their shares (dump), the price typically falls. Wrongdoers mainly target small capitalization stocks with low liquidity ("penny stocks") traded in the OTC market (Aggarwal and Wu, 2006). Although pump-and-dump schemes have existed for many decades, the emergence of the Internet and social media has provided a fertile new ground for fraudsters. False or misleading information can now be disseminated to a large number of potential investors with minimum effort, anonymously, and at a relatively low cost.[1] According to the Security and Exchange Commission (SEC)[2], "investors who learn of investing opportunities from social media should always be on the lookout for fraud." Indeed, social media is a very attractive channel for manipulators and stock promoters as it allows them to target a wide unsophisticated audience, more prone to being scammed than sophisticated investors. The anonymity of social media and the ease with which fake accounts and/or bots can be used to spam the network also facilitate fraudsters' activities.

In this paper, we extend the literature on indirect empirical evidence of market manipulation

[1] "Investor Alert: Social Media and Investing - Avoiding Fraud" - Security and Exchange Commission, January 2012

[2] "Updated Investor Alert: Social Media and Investing - Stock Rumors" - Security and Exchange Commission, November 2015

by analyzing data from one of the largest worldwide social media platforms: Twitter. While empirical proofs of market manipulation on small capitalization stocks have been identified using data from stock spam (e-mails) recommendations (Böhme and Holz, 2006; Frieder and Zittrain, 2007; Hanke and Hauser, 2008; Nelson et al., 2013) and messages boards (Sabherwal et al., 2011), pump-and-dump schemes on social media have, to the best of our knowledge, never been empirically studied. Fake news on Twitter can influence political, economic, and social well-being (Allcott and Gentzkow, 2017; Vosoughi et al., 2018). However, little is known about the prevalence of financial fake news on social media and its impact on stock markets. Due to the large number of messages and the ability to analyze users' characteristics and emotions, focusing on data from Twitter can provide new insights to the literature on market manipulation.

To explore the relation between the social media activity and small capitalization stock returns, we construct a novel database by collecting all messages posted on Twitter containing the ticker of a list of more than 5,000 small-capitalization stocks. We gather data in real time during a 11-month period to avoid issues related to deleted accounts or deleted tweets (ex post). Our final database is composed of 7,196,307 tweets posted by 248,748 distinct users.

We first conduct an event study to analyze the impact of a spike in posting activity on Twitter on the returns of small capitalization stocks. We find that an abnormally high message activity on social media about a company is associated with a sharp increase in abnormal trading volume from two days before the event up to five days after the event. We also find significant positive abnormal returns on the event day and on the day before the event, and a significant price reversal during the next five trading days. While the price pattern identified in the event study can be related to a pump-and-dump scheme (manipulation hypothesis), it could also be simply caused by overoptimistic noise traders (behavioral hypothesis) or by news / press releases (overreaction to news). To disentangle between the three hypotheses, we then conduct cross-sectional regressions. For each event, we examine users' characteristics to assess if the event was (partially) generated by the tweeting activity of stock promoters or by the tweeting activity of accounts dedicated to tracking pump-and-dump-schemes. After controlling for company characteristics (market capitalization, market type, percentage of non-trading days...), press releases, lagged returns, sentiment and total tweeting activity, we find that the price reversal pattern is much stronger when the events are generated by the tweeting activity of stock promoters and by the tweeting activity of accounts dedicated to tracking pump-and-dump-schemes. Overall, our findings favor the manipulation hypothesis over the behavioral hypothesis, and shed light on the need for a higher control of the information published on social media and better education for investors seeking trading opportunities on the Internet.

Our paper is organized as follows. Section 2 briefly reviews the theoretical and the empirical literature on market manipulation. Section 3 describes our database. Section 4 shows the results of the event study. Section 5 examines the relation between users' characteristics and stock returns, using both contemporaneous and predictive cross-sectional regressions. Section 6 presents some robustness checks. Section 7 concludes.

2. Related literature and hypothesis

Market manipulation undermines economic efficiency both by making prices less accurate as signals for efficient resource allocation and by making markets less liquid for risk transfer (Kyle and Viswanathan, 2008). Despite the importance of fair and transparent markets, little is know about the prevalence and impact of market manipulation (Putniņš, 2012). Theoretical studies have shown that traders can generate profits through trade-based manipulation (Allen and Gale, 1992) or information-based manipulation (Bommel, 2003). However, like any illegal behavior, market manipulation is not directly observable, and empirical studies remain very scarce. Owing to this lack of available data, a first strand of the literature focus on reported manipulation cases.

Studying all cases pursued by the Security and Exchange Commission from January 1990 to October 2001, Aggarwal and Wu (2006) present an extensive review of stock market manipulation in the United States. They find that around 50% of the manipulated stocks are small capitalization stocks (penny stocks) quoted in the OTC markets, such as the OTC Bulletin Board and the Pink Sheets. With regard to techniques used by fraudsters, more than 55% of cases involve spreading rumors or false information. Manipulators also frequently use wash trades and nominee accounts to create artificial trading activity. More recently, and using a database of 421 German pump-and-dump schemes between 2002 and 2015, Leuz et al. (2017) find that information-based market manipulation are quite common (6% of investors have participated in at least one pump-and-dump in their sample) and involve sizable losses for market participants (average loss of 30%).

However, only a small fraction of manipulation is detected and prosecuted (Comerton-Forde and Putniņš, 2014). Further, focusing on reported cases tends to create a selection bias toward unsophisticated manipulation and is affected by the regulators' agenda (Bonner et al., 1998). Hence, another strand of the literature focuses on indirect evidences by studying abnormal market behaviors (for trade-based manipulation) or by detecting suspicious behaviors outside the market (for information-based manipulation).

Analyzing intraday volume and order imbalance, Ben-Davis et al. (2013) show evidence suggesting that some hedge funds manipulate stock prices on critical reporting dates. Their findings are consistent with those of Carhart et al. (2002) on end-of-quarter manipulation by mutual funds. In line with this study, a nascent strand of the literature focuses on information-based manipulation by analyzing new datasets of stock spams (newsletters) sent by fraudsters trying to pump the value of a stock. Böhme and Holz (2006), Frieder and Zittrain (2007), and Hanke and Hauser (2008) find a significant positive short-run price impact after a stock spam touting, followed by a price reversal over the following days. Similar patterns have been observed when Internet message board activity is used to identify pump-and-dump scheme on small stocks without fundamental news (Sabherwal et al., 2011). In contrast, and using detailed data on the information contained in the spam messages, Nelson et al. (2013) find that stock spams lead to trading activity, but not a median price reaction.

In this paper, we explore the relation between the social media activity and small capitalization stock returns by focusing on a new channel of communication: Twitter. We hypothesize that a high number of messages about a company on Twitter should be associated with a contemporaneous increase in the price of the stock, followed by a price reversal over the next trading days. While this pattern could be consistent with market manipulation, it could also simply be caused by overoptimistic sentiment-driven noise trader. We thus hypothesize that if the price pattern is related to market manipulation or to stock promotion (pump-and-dump), the price reversal should be greater when the abnormal activity on Twitter is due to the tweeting activity of stock promoters or to the tweeting activity of accounts tracking pump-and-dump-schemes. In that regard, examining Twitter users' characteristics provides a unique framework allowing us to analyze more precisely the role of stock promoters and the impact of suspicious stock recommendations.

3. Data

3.1. The OTC Markets Group

Following findings from Aggarwal and Wu (2006), we focus our attention on stocks quoted by the OTC Markets Group. The OTC Markets Group is an electronic inter-dealer quotation and trading system providing marketplaces for around 10,000 OTC securities. The OTC Markets Group organizes securities into three tiered marketplaces: OTCQX, OTCQB, and OTC Pink. The marketplace on which a company trades reflects the integrity of its operations, its level of disclosure, and its degree of investor engagement.

- OTCQX marketplace: Companies must meet high financial standards, be current in their disclosure, and receive third party advisory.
- OTCQB marketplace: Companies must be current in their reporting, meet a minimum bid test of $0.01, and undergo an annual verification and management certification process.
- OTC Pink marketplace: Open to all companies. The OTC Pink is divided into three sub-

categories based on the quantity and quality of information provided to investors: current information, limited information, and no information.

We download the list of all Common Stock and Ordinary Shares of companies incorporated in the United States, excluding American Depository Receipts, ETF, Funds, and Warrants. Our sample consists of 5,087 companies: 61 (1.20%) are quoted on OTCQX, 1,858 (36.52%) on OTCQB, and 3,168 (62.28%) on OTC Pink. Among the companies listed on OTC Pink, 814 provide current information, 403 provide limited information, and 1,951 provide no information. Companies in the last category should, according to the OTC Markets Group "be treated with suspicion and their securities should be considered highly risky."

We use Bloomberg to download daily price data, traded volume data, and market capitalization for all 5,087 stocks. During the sample period, the vast majority of the stocks experienced a sharp decrease in price with a number of stocks losing nearly all their value. This finding is consistent with the finding reported by Ang et al. (2013) that over a long period, comparable listed-stocks tend to overperform OTC stocks by nearly 9% per year. However, a few stocks also showed impressive returns over the sample period. For example, the price of Micro Imaging Technology increased from $0.0229 to $0.45 between October 2014 and October 2015 (+1,865%). As documented by Eraker and Ready (2015), the returns of OTC stocks are negative on average and highly positively skewed, with a few "lottery-like" stocks doing extremely well while many of the stocks become worthless.

3.2. Twitter data

Twitter is a micro-blogging platform that enables users to send and read short 140-character messages called "tweets". Every day, more than 500 million messages are posted on Twitter. We develop a computer program in the Python programming language to collect data in real time using the Twitter Search Application Programming Interface (API). Precisely, using the Twitter "cashtag" feature, introduced in 2012, we extract all the messages containing a "$" sign followed by the ticker name, as in Sprenger et al. (2014b). As in Sprenger et al. (2014a), we query the API with each keyword (company cashtag) every hour to ensure that we collect all tweets during our sample period.

In the course of our sample period from October 5, 2014, to September 1, 2015, we collected a total of 7,196,307 tweets. Among the 5,087 companies, around 50% received a very low level of attention (between 0 and 20 tweets). On the other hand, four companies featured in more than 100,000 tweets: Tykhe Corp (*$HALB*), Cardinal Energy Group (*$CEGX*), Sterling Consolidated (*$STCC*) and Arrayit Corp (*$ARYC*). Table 1 presents descriptive statistics for the top 10 most discussed companies in the sample period. Overall, we find that Twitter activity is higher for companies listed on the OTC Pink marketplace, with a low stock price (penny stocks) and a small market capitalization.

[**Insert Table 1 about here**]

By analyzing the Twitter messages for the ten most discussed companies in our sample, we identified many fake Twitter accounts (bots) posting exactly the same type of messages at different periods, simply by replacing a ticker with another and changing a few keywords over time. After a certain period of abnormally high posting activity, the number of tweets reduced to a level close to zero. While it is difficult to ascertain if those bursts in social media activity are directly linked with attempts to manipulate the market, the use of multiple fake accounts to recommend buying a stock is at least suspicious.

The case of Wholehealth Products, Inc. (*$GWPC*), the eight most-discussed stock in our sample, is especially interesting. On November, 20, 2014, the Security Exchange Commission suspended trading on GWPC because of concerns regarding the accuracy and adequacy of publicly disseminated information by the company, including information about the relationship between the company's business prospects and the current Ebola crisis.[3] By examining the number of messages containing the ticker *$GWPC* posted on Twitter before the SEC halt, we identify a sharp

[3] "SEC Suspends Trading in Companies Touting Operations Related to Prevention or Treatment of Ebola", November 20, 2016

increase in posting activity starting on October 27th (Figure 1). A total of 2,774 tweets were sent on that day, compared to an average of less than 30 messages per day on the week before. The spike in posting activity on Twitter was followed by a one-week increase in stock price and a sharp price reversal afterward.

[**Insert Figure 1 about here**]

This anecdotal example is typical of a pump-and-dump scheme. A false piece of information is shared on Twitter to generate a spike in the social media activity about a given company. Stock price increases (pump) over a short period, and decreases sharply (dump) afterward. In the next section, we conduct an event study to analyze if the price reversal pattern identified anecdotally in the *$GWPC* case can be generalized. We do so by analyzing the link between an abnormally high activity on social media and OTC stocks returns.

4. Event study

Following Tumarkin and Whitelaw (2001) and Leung and Ton (2015), we define event days as follows: when the number of messages posted on Twitter about company i during a given day t exceeds the yearly average plus two standard deviations. To account for the regular operational hours of the exchanges, we consider all messages sent between 4 p.m. on day t-1 and 4 p.m. on day t as pertaining to day t. To reduce error introduced by stocks with very low tweeting activity or very illiquid stocks, we impose as event criteria a minimum of 20 tweets[4] and a minimum market capitalization of $1,000,000. If an event is detected on a non-trading day, we consider the next trading day as the event day. We also impose a minimum of 20 trading days between two events to avoid contagion on the event window.

[4] Tumarkin and Whitelaw (2001) and Leung and Ton (2015) impose a minimum of 10 message postings. We impose a higher threshold as the level activity is much higher on Twitter than on messages boards. Our results are robust to the threshold used.

The following example illustrates our methodology using a specific company: UBIQ Inc, (*$UBIQ*). During the sample period, a total of 1,048 messages containing the ticker *$UBIQ* were posted on Twitter. We identify two events for *$UBIQ* company: on February 6, 2015 (385 messages) and August 27, 2015 (53 messages). Table 2 shows a sample of tweets related to February 6, 2015, event. The activity on Twitter on that day is typical of a stock promotion scheme, where tweets are sent by bots and stock promoters through multiple accounts. Examining manually the 47 distinct users who sent tweets on that day, we identify tweets sent by stock promoters (i.e., @JetPenny, from the website http://www.jetlifepennystocks.com/, and @WallStreetPenni, from the website http://www.wallstreetpennies.com/) and tweets sent by users tracking pump-and-dump schemes (@PUMPSandDumps and @ThePumpTracker). This example is typical of a pump-and-dump scheme, where fraudsters or stock promoters try to temporarily inflate the price of a small capitalization stocks by using Twitter as a new channel of communication. Two years later, on March 20, 2017, the Security and Exchange Commission temporarily suspended trading in the securities of Ubiquity due to "a lack of current and accurate information about the company because Ubiquity is delinquent in its requisite periodic filings with the Commission."[5]

[**Insert Table 2 about here**]

Using this methodology for all stocks in our sample, we identify a total of 635 events for 315 distinct companies. Then, for each event detected, we compute abnormal return for the estimation window [-260:-11] (L1 = 250 days) and event window [-10:+10] (L2 = 21 trading days).[6] To define abnormal return, we consider three models of normal return: a market return model, a constant mean return model, and a capital asset pricing model. We use the NASDAQ MicroCap Index as a benchmark of market return. We also consider raw returns, as in Nelson et al. (2013). For clarity, we will report our results only for the market return model, as we find that our results are robust

5 https://www.sec.gov/litigation/suspensions/2017/34-80275.pdf

6 On unreported robustness check, we find that our results are robust to a 6-month estimation window and a 11-day event window.

to all models of normal return.[7]

We test the significance of abnormal return during the event window by conducting a non-parametric Corrado (1989) rank test, making no assumption about the normality of the underlying data. We transform each abnormal return $AR_{i,t}$ to a rank variable $K_{i,t}$, by assigning to the day with the highest return over the complete window (estimation and event window) a rank of +271, to the day with the second highest return a rank of +270, and so on until we assign the lowest return a rank of 1. Tied ranks are treated by the method of midranks. To allow for missing returns, ranks are standardized by dividing by one plus the number of non-missing returns.

$$K_{i,t} = \frac{rank(AR_{i,t)}}{(1 + M_i)} \tag{1}$$

where M_i is the number of non-missing values for security i in L1 and L2. This yields order statistics for the uniform distribution with an expected value of one-half. The rank test statistic for day t (T_t) is equal to

$$T_t = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (K_{i,t} - 0.5)/S(U) \tag{2}$$

where N is equal to the number of events. The estimated standard deviation S(U) is defined on the estimation (L1) and event (L2) window as[8]

$$S(U) = \sqrt{\frac{1}{L_1 + L_2} \sum\nolimits_t \left[\frac{1}{\sqrt{N_t}} \sum_{i=1}^{N_t} (K_{i,t} - 0.5) \right]^2} \tag{3}$$

where N_t represents the number of non-missing returns in the cross-section of N-firms on day t.

We test the statistical significance of abnormal return on each day of the event window and on each 5-day rolling interval to identify a price reversal over a one week period. We also consider abnormal trading volume, defined as volume on a given day divided by the average volume on

[7] The bad-model problem is less serious for event study with short window as daily expected returns are close to zero (Fama, 1998).

[8] We also consider a multi-day version by multiplying by the inverse of the square root of the period's length.

the estimation window. Figure 2 presents abnormal return (AR) and cumulative abnormal return (CAR) during the [-10:+10] event window, where day 0 is defined as a day of abnormally high activity on Twitter. Figure 3 presents abnormal volume (AV). Tables 3 and 4 summarize the results.

[**Insert Figure 2, Figure 3, Table 3 and Table 4 here**]

As in Kim and Kim (2014), we identify a strong contemporaneous relationship between Twitter activity and stock price on the event day (*t0*). We find a significant abnormal return of +4.10% on the day before the event and a significant abnormal return of +6.88% on the the event day. This finding is consistent with that of Sabherwal et al. (2011) who reported an increase of +13.93% on the event day (and +4.91% on the day before the event), when an event was defined as an abnormal number of messages on the financial message board "TheLion.com". According to Sabherwal et al. (2011), the abnormal return on the day before the event suggests a two-day price momentum, which is consistent with a pre-event two-day pumping hypothesis. While we acknowledge that price momentum is a plausible explanation, this pattern could also be related to a lagged reaction of the tweeting activity. For example, we find some cases where users on Twitter start talking about a stock that has experienced a strong price increase on day t (from 9.30 a.m. to 4 p.m.) only after market close (after 4 p.m.). In that situation, our methodology will identify the event on day t+1, leading to an abnormal return on the day before the event.

More interestingly, we find a significant post-event price reversal. Cumulative abnormal return is statistically significant and negative during the five days following the event ([+1:+5] window), with a post-event cumulative decrease in abnormal return of -3.11%. This finding is in line with Sabherwal et al. (2011) who observed a significant post-event decrease in stock price of -5.4% over the five trading days following the event day. Three non-exclusive hypotheses can explain the price reversal pattern and the deviation from the efficient market hypothesis. First, we conjecture that social media can be used as a proxy of investor overoptimism. In a market driven by unsophisticated traders with limits to arbitrage, price can deviate temporarily from its fundamental values in the presence of irrational sentiment-driven noise traders. In such a case, the price reversal identified on OTC stocks is simply caused by "standard" investor sentiment, as explained by Tetlock (2007). Second, the price reversal could be driven by an overreaction to news. For example, if the increase in tweeting activity is contemporaneous to the publication of a press release by a company, then the increase on the event day can be caused by the news, and the price reversal could be related to an overreaction to the news on the event day. Last but not least, the sharp price increase on the event day might be caused by fraudsters or stock promoters pumping the price of targeted stocks, before dumping it on the following days after having made an illegal profit.

To partially isolate one hypothesis from the other, we conduct cross-section contemporaneous and predictive cross-sectional regressions, controlling for stock characteristics, lagged returns, sentiment and press releases.

5. Cross-Sectional Regressions

In this section, we examine if the tweeting activity can (1) explain the increase in contemporaneous return, and, more importantly, (2) predict the price reversal on the week following the event. To examine if price changes are rooted in manipulative promotion rather than over-optimism by investors, we test the three following hypotheses.

- The price increase on the event day is higher when at least one tweet was sent by a stock promoter. This would be consistent with stock promoters' activity pumping the price of a stock on the event day by sending false or misleading information on Twitter.
- The price reversal after the event is higher when at least one tweet was sent by a stock promoter on the event day. This would be consistent with stock promoters selling the stock at an artificially inflated prices after the pumping period, and stock price reverting to its fundamental value.
- The price increase on the event day is lower when at least one tweet was sent by a user tracking

pump-and-dump schemes on the event day. This would be consistent with pump-and-dump trackers' activity mitigating the price increase on the event day by alerting users on Twitter of a potential pump-and-dump scheme.

Regarding the first hypothesis, we define manually a list of 156 stock promoters / paid advertisers by analyzing the tweeting activity of all users from our database with a minimum of 100 tweets (7,069 users). We define as a stock promoter all users with a reference to a promotion website or a promotional newsletter in their description. We also analyze all tweets containing the following keywords: "newsletter", "paid", "tout", "promote", "promotion", "promoter", "compensate", "compensation", "advert", "advertiser", "disclaimer", "disclosure", "investor relation", and we manually flag all stock promoters.[9] For each event, we create a dummy variable denoted $StockPromoter_t^i$ equal to 1 if at least one tweet was sent by a stock promoter from our list, and equal to 0 otherwise. Considering all events in our sample (635), we identify at least one stock promoter for 403 events (63.46%).

Examining users' characteristics, we also identify two users whose tweeting activity is dedicated to tracking pump-and-dump schemes: "*@ThePumpTracker*" and "*@PUMPSandDUMPS*". Those two accounts are, according to their own description, dedicated to "track pump and dump's, pump promotions, chatroom pumps, scams, ICO scams, crypto scams" and publish a message on Twitter to alert individual investors every time they suspect that a stock is under manipulation. For each event, we create a dummy variable denoted $PumpTracker_t^i$ equal to 1 if at least one tweet was sent by *@ThePumpTracker* or by *@PUMPSandDUMPS* on the event day, and equal to 0 otherwise. Considering all events in our sample (635), we identify at least one user tracking pump-and-dump schemes for 57 events (8.98%)

The contemporaneous relation is tested using the following model, considering each of the 635 events defined previously as an observation:

[9] The list is available upon request.

$$
\begin{aligned}
AR_t^i = \alpha + \beta_1 AR_{t-1}^i + \beta_2 MarketCap_t^i + \beta_3 Price_t^i + \beta_4 NonTradingDays_t^i \\
+\beta_5 MarketType_t^i + \beta_6 Sentiment_t^i + \beta_7 News_t^i + \beta_8 NumberMessages_t^i \\
+\beta_9 StockPromoter_t^i + \beta_{10} PumpTracker_t^i + \beta_{11} IRAccount_t^i + \epsilon_t
\end{aligned} \tag{4}
$$

where, for each observation i, AR_t^i is the abnormal return on the event day, AR_{t-1}^i is the abnormal return on the day before the event, $MarketCap_t^i$ is the market capitalization at the beginning of the event window, $Price_t^i$ is the price of the stock at the beginning of the event window, $NonTradingDays_t^i$ is the percentage of non-trading days during the estimation window (percentage of days with zero trading volume), $MarketType_t^i$ is a dummy variable equal to 1 if the company is listed on the "Limited & No Information" OTC Pink marketplace, $News_t^i$ is a dummy variable equal to 1 if a press release was sent on the event day or on the day before the event, $Sentiment_t^i$ is the average sentiment of messages sent during the event day, $NumberMessages_t^i$ is the total number of message sent during the event day, $StockPromoter_t^i$ is a dummy variable equal to 1 if at least one tweet was sent on the event day by an account on the "stock promoter list" defined previously, $PumpTracker_t^i$ is a dummy variable equal to 1 if at least one tweet was sent on the event day by an account dedicated to tracking pump-and-dump scheme, and $IRAccount_t^i$ is a dummy variable equal to 1 if the company had an official "Investor Relation" Twitter account at the date of the event.

Press releases are extracted from the "OTC Disclosure & News Service" on the OTC Market Group website. Sentiment is computed using Renault (2017) field-specific lexicon, derived from a large database of 750,000 classified messages published on the microblogging platform StockTwits. The lexicon contains a list of 543 positive terms and a list of 768 negative terms. Table 5 presents descriptive statistics for all variables. We find that 117 events are related to a day with a press release (18.43%). The 518 other event days (81.57%) are days without any fundamental news, as in the framework of Sabherwal et al. (2011). Regarding sentiment, we find that the average sentiment is positive for 539 events (84.88%) and negative or neutral for only 96 events (15.12%). As already documented in the literature (see, e.g., Kim and Kim, 2014; Avery et al., 2016), online investors are mostly bullish when sharing information about stock market on the Internet. Individual investors do not (typically) sell short, hold small portfolios and are net-buyer of attention-grabbing stocks (Barber and Odean, 2008). Thus, when individual investors talk about a stock on the Internet, they tend to post messages mainly about the stock they hold or the stock they want to buy using a bullish (positive) vocabulary. In this investigation, the bullishness bias can also be viewed as fraudsters trying to pump the price of a stock by sharing (false) positive information about a given company on social media.

Table 6 reports the results of the contemporaneous regression (Equation 4). We find that abnormal returns on the event day are positively related with social media sentiment and negatively related to market capitalization. These findings are similar to those of Sabherwal et al. (2011): same-day stock returns are higher for stocks with higher sentiment and smaller size. We also find that the percentage of non-trading days is negatively related to abnormal returns on the event day: returns are on average higher for illiquid penny stocks. Abnormal return on the event day are lower for stocks that have experienced higher abnormal return on the day before the event. As the coefficient on $News$ is not significantly different from zero, and as we demonstrate in the previous section that returns on the day before the event are large and significant, this finding could be related to the results of Savor (2012) who find that, after major price changes, no-information price events experience strong reversals. This situation would also be consistent with a lagged reaction of users on Twitter, as discussed previously.

We also find that adding variables related to user's tweeting activity significantly improve the accuracy of the model. On one hand, the tweeting activity of stock promoters is positively related to abnormal return on the event day, consistent with the "pump" period of a pump-and-dump scheme. On the other hand, the tweeting activity of users tracking pump-and-dump scheme is negatively related to abnormal return on the event day. When individuals investors are alerted that a stock might be under promotion, the impact on stock price on the event day is lower. Those results confirm our hypothesis of a "pumping" period associated with an abnormal tweeting activity on social media.

To examine if a "dumping" period follows the "pumping" period identified on the event day, we examine the predictive relation by using a model similar to Equation 4, replacing AR_t by $CAR_{t+1,t+n}$, where $n = 1, 2, ..., 10$. Table 7 reports the results of the predictive regressions (Equation 5).

$$\begin{aligned} CAR^i_{t+1,t+n} = \alpha &+ \beta_1 AR^i_t + \beta_2 MarketCap^i_t + \beta_3 Price^i_t + \beta_4 NonTradingDays^i_t \\ &+ \beta_5 MarketType^i_t + \beta_6 Sentiment^i_t + \beta_7 News^i_t + \beta_8 NumberMessages^i_t \\ &+ \beta_9 StockPromoter^i_t + \beta_{10} PumpTracker^i_t + \beta_{11} IRAccount^i_t + \epsilon_t \end{aligned} \tag{5}$$

We find that on average, the price reversal is higher for stocks that have experienced a strong price increase on the event day, consistent again with Savor (2012). Other variables, such as market capitalization, sentiment or press releases, are not significant and do not help predicting cumulative abnormal returns after the event day. Consistent with a pump-and-dump scheme, we find that the price reversal pattern is significantly stronger when the events are generated by the tweeting activity of stock promoters or by the tweeting activity of accounts dedicated to tracking pump-and-dump schemes. This finding is true for $1 <= n <= 10$. We also find that the price reversal is significantly lower (at the 10% confidence level) for firms with corporate social media accounts. This result is consistent with those in Blankespoor et al. (2013); firms with corporate social media accounts might be able to control the spread of fake news and thus reduce information asymmetry.

Overall, all those results favor the manipulation/promotion hypothesis over the behavioral hypothesis.

6. Robustness Tests

To assess the robustness of our results, we first conduct another event study by splitting our 635 events into "Promoter Event" and "No Promoter Event". We do so to analyze if the price reversal identified in Section 4 totally disappears for "No Promoter Event", which would be consistent with the efficient market hypothesis. Then, we examine if the number of retweets or the number of tweets with an external links improve the accuracy of our model. We do so to examine if the tweeting activity by fake accounts (bots) affects the phenomenon, as bots mostly publish messages with an external links to their own website, while traders do not (and bots very rarely retweets messages from other users, while traders do). Last, and following a SEC Investor Alert warning investors about potential risks involving investments in marijuana-related companies in May 2014[10], we analyze if our events are associated with marijuana-related companies and we examine the pattern of abnormal returns around events related to those companies.

As shown in the previous section, the price reversal is higher when the events are generated by the tweeting activity of stock promoters or by the tweeting activity of accounts dedicated to tracking pump-and-dump schemes. Thus, we conduct two event studies, using the same methodology as previously, but considering (1) all events without any tweets by a stock promoter nor by a user tracking pump-and-dump schemes (228 events - "No Promoter Event"), (2) all events with at least one tweet by a stock promoter or one tweet from a user tracking pump-and-dump schemes (407 events - "Promoter Event"). We do not identify any significant price reversal when we consider "No Promoter" events. We even find the opposite pattern, as abnormal return increases on average by 0.87% on the five days following the event. On the other hand, we find a very strong and significant price reversal when we focus on "Promoter Event". Abnormal return decreases on average by 5.34% on the five days following the event. Table 8 presents the results.

We also analyze (1) if tweets containing links are more/less credible than tweets without links, (2) if tweets with a lot of retweets are more/less credible than other tweets. We denote *PctRetweet*

[10] https://www.sec.gov/oiea/investor-alerts-bulletins/ia_marijuana.html

the number of retweets divided by the total number of tweets sent on the event day, and *PctLink* the number of tweets containing a link divided by the total number of tweets sent on the event day. We also consider the number of distinct users and the number of tweets containing a mention. None of these variable improve the accuracy of the model, neither on the contemporaneous regression nor on the predictive regression. Table 9 presents the results.

Last, we examine if the abnormal return on the event day and the price reversal on the next trading week is more pronounced for stocks that have been classified "at risk" by the Security and Exchange Commission. On May 7, 2014, the SEC has released an investor alert to make investors aware about the potential risks of investments involving Bitcoin and other forms of virtual currency. On May 16, 2014, another investor alert was released about the risks of marijuana-related companies, and on November 20, 2014, about companies that claim their products or services relate to Ebola. We find that, while "bitcoin stocks" and "ebola stocks" only represent a minor percentage of the events (respectively 1.1% and 2.52%), the number of events related to "marijuana stocks" is very large (122 events out of a total of 635)[11]. We create a dummy variable $Marijuana_t$ equal to 1 if at least one tweet contains a keyword related to this topic. Adding the variable $Marijuana_t$ to our model, we find that the price reversal is significantly higher (at the 10% level) for marijuana-related stocks. Table 9 presents the results.

The two variables *StockPromoter* and *PumpTracker* are significant in all our robustness checks. Overall, our findings are consistent with the patterns of a pump-and-dump scheme, where fraudsters/promoters use social media to temporarily inflate the price of small capitalization stocks.

7. Conclusion

Social media can help investors gather and share information about stock markets. However, it also presents opportunities for fraudsters to send false or misleading statements in the marketplace.

[11] More precisely, we consider the root "bitcoin" and "crypto" for the variable $Bitcoin_t$, "marijuana" and "cannabis" for $Marijuana_t$, and "ebola" for $Ebola_t$

In that regard, the social media platform Twitter is a very attractive channel for manipulators or stock promoters as it allows them to target a wide unsophisticated audience, more prone to being scammed than sophisticated investors. The anonymity of Twitter and the ease with which fake accounts and/or bots can be used to spam the network also facilitate fraudsters' activities.

In this paper, we provide, to the best of our knowledge, the first empirical evidence showing that fraudsters can use social media to artificially inflate the price of a stock. Defining an event as an abnormally high posting activity on Twitter about a company, we identify a large increase in stock price on the event day, followed by a sharp price reversal over the next five trading days. Examining users' characteristics, and controlling for lagged abnormal returns, press releases, sentiment and firms' characteristics, we find that the price reversal pattern is stronger when the events are generated by the tweeting activity of stock promoters or by the tweeting activity of accounts dedicated to tracking pump-and-dump schemes.

While a judicial inquiry would be needed to assess if the promotion scheme where legal or not, our findings shed light on the need for higher control over the information published on social media and better education for investors seeking trading opportunities on the Internet. Given the risk of manipulation and the average negative return of OTC stocks, individual investors should be very cautious when choosing to invest on risky and illiquid small capitalization stocks.

References

Aggarwal, R., Wu, G., 2006. Stock market manipulations. The Journal of Business 79, 1915–1954.

Allcott, H., Gentzkow, M., 2017. Social media and fake news in the 2016 election. Journal of Economic Perspectives 31, 211–36.

Allen, F., Gale, D., 1992. Stock-price manipulation. Review of Financial Studies 5, 503–529.

Ang, A., Shtauber, A. A., Tetlock, P. C., 2013. Asset pricing in the dark: The cross-section of OTC stocks. Review of Financial Studies 26, 2985–3028.

Avery, C. N., Chevalier, J. A., Zeckhauser, R. J., 2016. The "CAPS" prediction system and stock market returns. Review of Finance 20, 1363–1381.

Barber, B. M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785–818.

Ben-Davis, I., Franzoni, F., Landier, A., Moussawi, R., 2013. Do hedge funds manipulate stock prices? The Journal of Finance 68, 2383–2434.

Blankespoor, E., Miller, G. S., White, H. D., 2013. The role of dissemination in market liquidity: Evidence from firms' use of Twitter. The Accounting Review 89, 79–112.

Böhme, R., Holz, T., 2006. The effect of stock spam on financial markets. Working Paper, Technische Universität Dresden .

Bommel, J. V., 2003. Rumors. The Journal of Finance 58, 1499–1520.

Bonner, S. E., Palmrose, Z.-V., Young, S. M., 1998. Fraud type and auditor litigation: An analysis of SEC accounting and auditing enforcement releases. Accounting Review 73, 503–532.

Carhart, M. M., Kaniel, R., Musto, D. K., Reed, A. V., 2002. Leaning for the tape: Evidence of gaming behavior in equity mutual funds. The Journal of Finance 57, 661–693.

Comerton-Forde, C., Putniņš, T. J., 2014. Stock price manipulation: Prevalence and determinants. Review of Finance 18, 23–66.

Corrado, C. J., 1989. A nonparametric test for abnormal security-price performance in event studies. Journal of Financial Economics 23, 385–395.

Eraker, B., Ready, M., 2015. Do investors overpay for stocks with lottery-like payoffs? An examination of the returns of OTC stocks. Journal of Financial Economics 115, 486–504.

Fama, E. F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283–306.

Frieder, L., Zittrain, J., 2007. Spam works: Evidence from stock touts and corresponding market activity. Hastings Communications and Entertainment Law Journal 30, 479.

Hanke, M., Hauser, F., 2008. On the effects of stock spam e-mails. Journal of Financial Markets 11, 57–83.

Kim, S.-H., Kim, D., 2014. Investor sentiment from Internet message postings and the predictability of stock returns. Journal of Economic Behavior & Organization 107, 708–729.

Kyle, A. S., Viswanathan, S., 2008. How to define illegal price manipulation. The American Economic Review 98, 274–279.

Leung, H., Ton, T., 2015. The impact of Internet stock message boards on cross-sectional returns of small-capitalization stocks. Journal of Banking & Finance 55, 37–55.

Leuz, C., Meyer, S., Muhn, M., Soltes, E., Hackethal, A., 2017. Who falls prey to the Wolf of Wall Street? Investor participation in market manipulation. Working Paper 24083, National Bureau of Economic Research.

Nelson, K. K., Price, R. A., Rountree, B. R., 2013. Are individual investors influenced by the optimism and credibility of stock spam recommendations? Journal of Business Finance & Accounting 40, 1155–1183.

Putniņš, T. J., 2012. Market manipulation: a survey. Journal of Economic Surveys 26, 952–967.

Renault, T., 2017. Intraday online investor sentiment and return patterns in the US stock market. Journal of Banking & Finance 84, 25–40.

Sabherwal, S., Sarkar, S. K., Zhang, Y., 2011. Do Internet stock message boards influence trading? Evidence from heavily discussed stocks with no fundamental news. Journal of Business Finance & Accounting 38, 1209–1237.

Savor, P. G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics 106, 635–659.

Sprenger, T. O., Sandner, P. G., Tumasjan, A., Welpe, I. M., 2014a. News or noise? Using Twitter to identify and understand company-specific news flow. Journal of Business Finance & Accounting 41, 791–830.

Sprenger, T. O., Tumasjan, A., Sandner, P. G., Welpe, I. M., 2014b. Tweets and trades: The information content of stock microblogs. European Financial Management 20, 926–957.

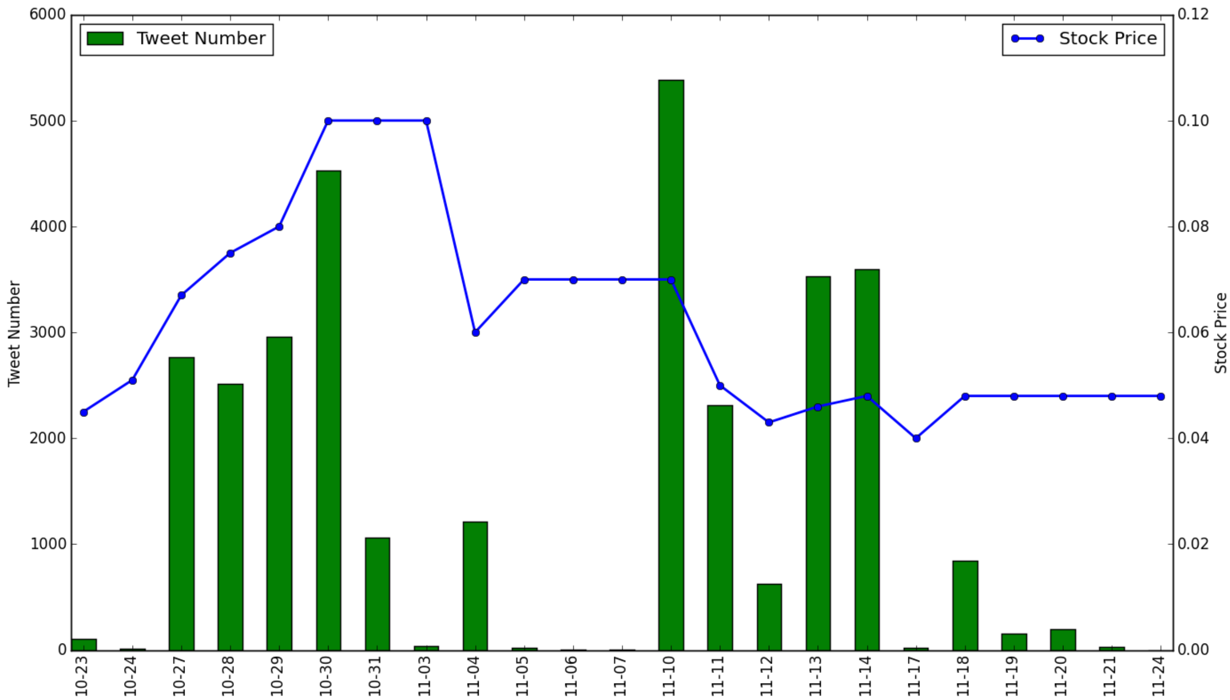
Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance 62, 1139–1168.

Tumarkin, R., Whitelaw, R. F., 2001. News or noise? Internet postings and stock prices. Financial Analysts Journal 57, 41–51.

Vosoughi, S., Roy, D., Aral, S., 2018. The spread of true and false news online. Science 359, 1146–1151.

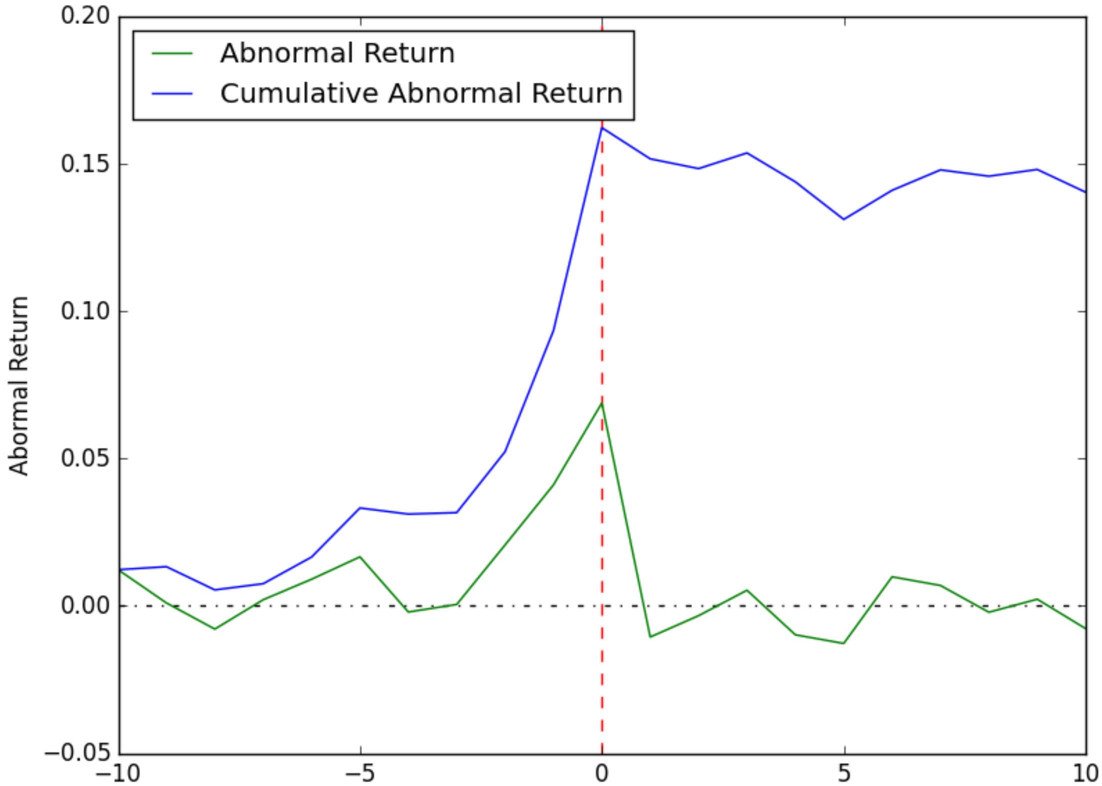
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: Journal of the Econometric Society pp. 817–838.

Fig. 1. Wholehealth Products, Inc ($\$GWPC$) - Stock price and Twitter activity



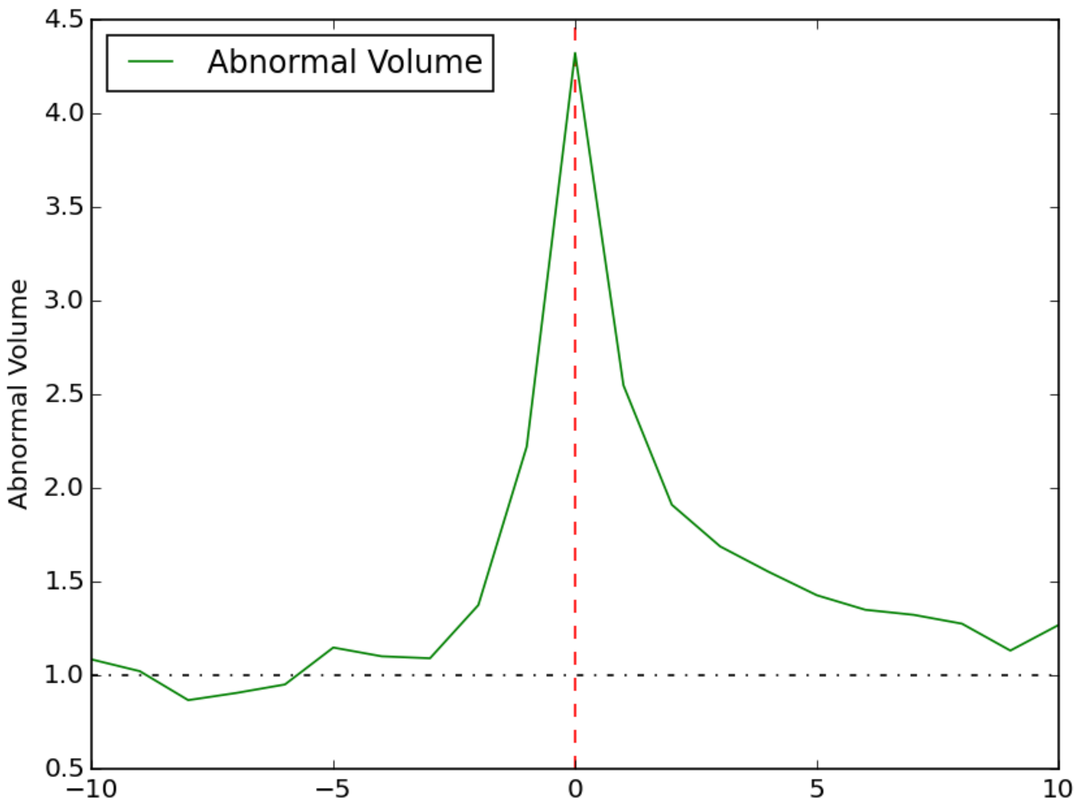
Notes: This figure shows the price of the Wholehealth Products ($\$GWPC$) shares (right-axis) and the daily number of messages containing the cashtag $\$GWPC$ posted on Twitter between October 23, 2014, and November 24, 2014 (left-axis). Due to the SEC investigation, $GWPC stock price is flat at $0.048 between November 20, and November 24. $\$GWPC$ stock price drops to $0.0001 when trading resumes on December 23, 2014.

Fig. 2. Event Study - Abnormal returns and cumulative abnormal returns



Notes: This figure shows the abnormal returns and the cumulative abnormal returns on a [-10:+10] days event window. Events are defined as an abnormally high tweeting activity on social media. Average abnormal returns and cumulative average abnormal returns are computed on a total of 635 events about 315 distinct companies.

Fig. 3. Event Study - Abnormal volume



Notes: This figure shows the abnormal volume on a [-10:+10] days event window. Events are defined as an abnormally high tweeting activity on social media. Abnormal volume is computed on a total of 635 events about 315 distinct companies.

Table 1: Top 10 most discussed OTC Markets stocks on Twitter

Ticker	Company	Market	Disclosure	Tweet Number	Stock Price	Market Cap
$HALB	Tykhe Corp	OTC Pink	Current	397,098	0.01	#NA
$CEGX	Cardinal Energy Group	OTC Pink	Current	169,263	0.8	28.14
$STCC	Sterling Consolidated	OTC Pink	Limited	143,572	0.045	1.81
$ARYC	Arrayit Corp	OTCQB	#NA	104,683	0.1624	6.43
$GPDB	Green Polkadot Box	OTC Pink	Current	93,352	1.85	19.75
$MINE	Minerco Resources	OTC Pink	Current	80,330	0.7813	19.04
$MYEC	MyEcheck	OTC Pink	Current	49,940	0.0202	81.00
$GWPC	Wholehealth Products	OTC Pink	Limited	36,500	0.25	19.92
$PUGE	Puget Technologies	OTCQB	#NA	32,797	0.0556	2.36
$CELH	Celsius Holdings	OTC Pink	Current	31,041	0.5283	9.78

Notes: This table presents the number of messages published on Twitter between October 5, 2014, and September 1, 2015, for the 10 most discussed stocks in our sample. Stock price (in USD) and market capitalization (in million USD) as of October, 1, 2014. #NA is used to indicate when information is not provided by Bloomberg.

Table 2: Messages containing the cashtag $UBIQ posted on Twitter on February 6, 2015.

Date	User	Message content
2015-02-05 16:40:35	pickoftheday1	$UBIQ Nice days here today Ubiquity Inc. QB UBIQ 0.729 + 0.159 27.89% Volume: 157 453 @ 4:05:55 PM ET [url]
2015-02-05 16:42:44	cabroncita	UBIQ Nice green close today!! Put this one on your radar! $UBIQ [url]
2015-02-05 16:46:14	cabroncita	$UBIQ Company Website [url]
2015-02-05 16:51:04	JetPenny	Cabroncita: $UBIQ Company Website [url]
2015-02-05 16:59:37	iHangout4	cherrob: The Hunt for the Next 10 Bagger: $UBIQ Nice days here today Ubiquity Inc. QB [url]
2015-02-05 16:59:38	iHangout4	cherrob: BREAKOUTS..RUNNERS AND HOT PENNIES: $UBIQ Nice days here today Ubiquity Inc. QB [url]
2015-02-05 17:01:46	Hot_pennyalert	budfoxhub: $UBIQ +27% big close today bull run starting! [url]
2015-02-05 17:20:54	cabroncita	$UBIQ Check out their patents! http://t.co/ckhN8B36yB
2015-02-05 17:47:36	ThePUMPTracker	Alert : http://t.co/zVyxyqFLK7 announces $UBIQ as 02/06/2015 promo.Get the detailed promo [url]
2015-02-05 17:50:46	PennyStocksBlog	RT @ThePUMPTracker: Alert : [url] announces $UBIQ as 02/06/2015 promo.Get the detailed promo alert at [url]
2015-02-05 19:31:49	Pubcos	$UBIQ seams to be building. Looks like there could be some momentum. Let s see...
2015-02-05 19:35:16	Pubcos	$UBIQ new entertainment amp communications experience creators amp viewers together combining television [url].
2015-02-05 19:38:08	Pubcos	Information is power. You may want to put this company on your radar: [url] $UBIQ... Pubcos UBIQ MoneyTeam
2015-02-05 19:42:48	Pubcos	$UBIQ +27% growth today. Congrats....
2015-02-06 09:01:32	PUMPSandDUMPS	Before you get taken by today s $UBIQ pump you better review the ticker s Past Performances [url]
2015-02-06 09:25:39	StockPromoters	$UBIQ StockPromoters.com http://t.co/v3yEIMowcM
2015-02-06 09:27:31	hecklerhouse	$UBIQ chatter chatter
2015-02-06 10:43:25	WallStreetPenni	Mick Dodge: $UBIQ is working hard to create a diverse [url]
2015-02-06 10:43:26	WallStreetPenni	Affix Trader: $UBIQ Ubiquity is focused in five specific areas.... [url]
2015-02-06 10:51:09	JetPenny	Affix Trader: $UBIQ Don t miss their patent portfolio overview! IP [url]
2015-02-06 15:15:29	explodeprofits	DITRstocks: $UBIQ Short Term Indicators Barchart Opinion [url] [url]
2015-02-06 15:17:05	JetPenny	DITRstocks: $UBIQ Short Term Indicators Barchart Opinion [url]

Notes: This table presents a sample of messages containing the cashtag *$UBIQ* posted on Twitter between February 5, 2015 (after market close) and February 6, 2015 (before market close). The messages include tweets sent by stock promoters (i.e., @JetPenny, from the website http://www.jetlifepennystocks.com/, and @WallStreetPenni, from the website http://www.wallstreetpennies.com/) and tweets sent by users tracking pump-and-dump schemes (@PUMPSandDumps and @ThePumpTracker). This example is typical of a pump-and-dump scheme, where fraudsters or stock promoters try to temporarily inflate the price of a small capitalization stocks by using Twitter as a new channel of communication.

Table 3: Event-Study Results - Abnormal Return and Abnormal Volume

Day	Abnormal Return (%)	Abnormal Volume
-10	1.2288	1.0843
-9	0.1003	1.0213
-8	-0.7860	0.8668
-7	0.2093	0.9053
-6	0.9044	0.9505
-5	1.6631	1.1477
-4	-0.2072	1.1008
-3	0.0497	1.0903
-2	2.0686	1.3745
-1	4.1035***	2.2205
0	6.8796***	4.3223
1	-1.0551*	2.5479
2	-0.3310*	1.9102
3	0.5308	1.6875
4	-0.9802*	1.5522
5	-1.2729	1.4268
6	0.9869	1.3493
7	0.6920	1.3223
8	-0.2144	1.2750
9	0.2277	1.1315
10	-0.7696	1.2683
Event Number	635	635

Notes: This table shows the abnormal returns and the abnormal volumes on a [-10:+10] days event window around the event day (*t0*). ***, ** and * represent abnormal returns significance, respectively at the 1%, 5%, and 10% level using a Corrado rank test.

Table 4: Event-Study Results - Cumulative Abnormal Returns (5-day)

Dates	5-day CAR (%)
$[-10:-6]$	1.6569
$[-9:-5]$	2.0912
$[-8:-4]$	1.7837
$[-7:-3]$	2.6193
$[-6:-2]$	4.4786
$[-5:-1]$	7.6776***
$[-4:0]$	12.8942***
$[-3:1]$	12.0462***
$[-2:2]$	11.6656***
$[-1:3]$	10.1278***
$[0:4]$	5.0441
$[1:5]$	-3.1085***
$[2:6]$	-1.0664**
$[3:7]$	-0.0434*
$[4:8]$	-0.7886***
$[5:9]$	0.4193**
$[6:10]$	0.9226**
Event Number	635

Notes: This table shows the cumulative abnormal returns at 5-day intervals in a [-10:+10] days event window around the event day (*t0*). ***, ** and * represent abnormal returns significance respectively at the 1%, 5%, and 10% level using a Corrado rank test.

Table 5: Descriptive Statistics

Variable	Mean	Median	Min	Max	Std-Dev
AR_t	0.0688	0.0142	-0.7731	1.9837	0.2386
$CAR_{t+1;t+5}$	-0.0311	-0.0306	-0.9673	1.4782	0.2365
$MktCap_t$	196.2422	9.3357	1.0011	15037.7915	1278.4197
$Price_t$	2.1342	0.1225	0.0001	168.75	8.3172
$NonTradingDays_t$	0.0508	0.0	0.0	0.8571	0.1269
$MktType_t$	0.126	0.0	0.0	1.0	0.3321
$Sentiment_t$	0.3063	0.2727	-0.9436	1.0	0.317
$News_t$	0.1843	0.0	0.0	1.0	0.388
$MessageNumber_t$	192.5465	48.0	20.0	5250.0	514.5267
$StockPromoter_t$	0.6346	1.0	0.0	1.0	0.4819
$PumpTracker_t$	0.0898	0.0	0.0	1.0	0.2861
$IRAccount_t$	0.4961	0.0	0.0	1.0	0.5004

Notes: This table presents summary statistics for all variables used in the contemporaneous and predictive regressions. The sample includes a total of 635 observations (events), where t represents the event day (i,e. days with an abnormally high tweeting activity about company i).

Table 6: Contemporaneous Regression

Model	[1]		[2]		[3]	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	0.1296***	5.9237	0.0413	1.1532	0.0034	0.0890
AR_{t-1}	-0.2188***	-3.9294	-0.2268***	-4.0162	-0.2425***	-4.3619
$MktCap$	-0.0159***	-3.0639	-0.0136***	-2.6893	-0.0124**	-2.4930
$Price$	-0.0011*	-1.8117	-0.0011**	-2.0287	-0.0010	-1.4964
$NonTradingDays$	-0.1404**	-2.3708	-0.1149*	-1.9156	-0.0848	-1.4392
$MarketType$	-0.0213	-0.7907	-0.0097	-0.3643	-0.0128	-0.4909
$Sentiment$			0.0911***	3.3576	0.0865***	3.2003
$News$			0.0305	1.2926	0.0239	1.0336
$MessageNumber$			0.0110	1.4499	0.0109	1.4398
$StockPromoter$					0.0612***	3.4007
$PumpTracker$					-0.0948***	-3.2784
$IRAccount$					0.0144	0.7864
Adj-R^2 (%)	4.62		6.23		8.23	
Observations	635		635		635	

This table reports the results of the equation $AR_t^i = \alpha + \beta_1 AR_{t-1}^i + \beta_2 MarketCap_t^i + \beta_3 Price_t^i + \beta_4 NonTradingDays_t^i + \beta_5 MarketType_t^i + \beta_6 Sentiment_t^i + \beta_7 News_t^i + \beta_8 NumberMessages_t^i + \beta_9 StockPromoter_t^i + \beta_{10} PumpTracker_t^i + \beta_{11} IRAccount_t^i + \epsilon_t$. Standard errors are computed using White (1980) heteroskedasticity robust standard errors. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The regression includes 635 observations.

Table 7: Predictive Regressions

Model	[n=5]		[n=5]		[n=5]	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	-0.0239	-1.1423	-0.0009	-0.0212	0.0205	0.5100
AR_t	-0.1805***	-3.6333	-0.1814***	-3.5638	-0.1848***	-3.7125
$MktCap$	0.0026	0.5494	0.0026	0.5360	-0.0018	-0.3665
$Price$	0.0001	0.2700	0.0001	0.1700	-0.0001	-0.2062
$NonTradingDays$	0.0133	0.1995	0.0132	0.1966	0.0132	0.2017
$MarketType$	-0.0172	-0.5488	-0.0176	-0.5635	-0.0253	-0.8074
$Sentiment$			0.0161	0.5002	0.0097	0.3030
$News$			-0.0013	-0.0626	-0.0030	-0.1407
$MessageNumber$			-0.0065	-0.8569	-0.0035	-0.4615
$StockPromoter$					-0.0430**	-2.2386
$PumpTracker$					-0.0845***	-2.8325
$IRAccount$					0.0315*	1.6703
Adj-R^2 (%)	2.72		2.40		4.39	
Observations	635		635		635	

Model	[n=1]		[n=2]		[n=10]	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	-0.0045	-0.1982	0.0458	1.3415	0.1382**	2.2166
AR_t	-0.0665**	-2.2536	-0.1122***	-2.8144	-0.0909	-1.5180
$MktCap$	-0.0006	-0.2504	-0.0040	-1.0680	-0.0087	-1.1945
$Price$	0.0008**	2.2017	-0.0001	-0.2789	0.0012	0.4891
$NonTradingDays$	-0.0386	-1.0564	0.0058	0.1073	0.3447	1.6212
$MarketType$	-0.0274*	-1.7096	-0.0603**	-2.4085	0.0338	0.5947
$Sentiment$	-0.0008	-0.0448	0.0044	0.1933	-0.0096	-0.2396
$News$	-0.0017	-0.1360	-0.0132	-0.9674	0.0134	0.5047
$MessageNumber$	0.0059	1.2633	-0.0011	-0.1933	-0.0254**	-2.3697
$StockPromoter$	-0.0365***	-3.4556	-0.0414***	-2.6506	-0.1043***	-3.2928
$PumpTracker$	-0.0240*	-1.7447	-0.0729***	-3.9165	-0.0809**	-2.0453
$IRAccount$	0.0097	0.9502	0.0081	0.5626	0.0519*	1.6506
Adj-R^2 (%)	3.51		4.41		5.04	
Observations	635		635		635	

This table reports the results of the equation $CAR^i_{t+1,t+n} = \alpha + \beta_1 AR^i_t + \beta_2 MarketCap^i_t + \beta_3 Price^i_t + \beta_4 NonTradingDays^i_t + \beta_5 MarketType^i_t + \beta_6 Sentiment^i_t + \beta_7 News^i_t + \beta_8 NumberMessages^i_t + \beta_9 StockPromoter^i_t + \beta_{10} PumpTracker^i_t + \beta_{11} IRAccount^i_t + \epsilon_t$ for n=1, n=2, n=5 and n=10. Standard errors are computed using White (1980) heteroskedasticity robust standard errors. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The regression includes 635 observations.

Table 8: Event-Study Results - Cumulative Abnormal Returns (5-day)

Dates	Promoter Event (%)	No Promoter Events (%)
$[-10:-6]$	2.3640	0.3947
$[-9:-5]$	2.8565	0.7251
$[-8:-4]$	2.3922	0.6974
$[-7:-3]$	3.2668	1.4635
$[-6:-2]$	6.1218	1.5454
$[-5:-1]$	10.4945*	2.6493**
$[-4:0]$	17.2805***	5.0642***
$[-3:1]$	14.9200***	6.9163***
$[-2:2]$	14.0037***	7.4918***
$[-1:3]$	11.4892***	7.6975***
$[0:4]$	5.3457	4.5058
$[1:5]$	-5.3418**	0.8782*
$[2:6]$	-3.0545	2.4826**
$[3:7]$	-2.4034	4.1694
$[4:8]$	-3.0681***	3.2805
$[5:9]$	-1.8124**	4.4032
$[6:10]$	-1.3852**	5.0422
Number of Events	407	228

Notes: This table shows the cumulative abnormal returns at 5-day intervals in a [-10:+10] days event window around the event day ($t0$). "Promoter Event" are all events with at least one tweet by a stock promoter or one tweet from a user tracking pump-and-dump schemes (407 events). "No Promoter Event" are all events without any tweets by a stock promoter nor by a user tracking pump-and-dump schemes (228 events). Superscripts ***, ** and * represent abnormal returns significance, respectively at the 1%, 5%, and 10% level using a Corrado rank test.

Table 9: Predictive Regressions - Control Variables

Model	[1]		[2]		[3]	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	0.0051	0.1018	0.0161	0.4038	-0.0025	-0.0507
AR_t	-0.1806***	-3.6134	-0.1836***	-3.6842	-0.1787***	-3.5737
$MktCap$	-0.0016	-0.3116	-0.0020	-0.3999	-0.0017	-0.3311
$Price$	-0.0001	-0.1910	-0.0002	-0.4267	-0.0002	-0.4066
$NonTradingDays$	0.0112	0.1713	-0.0061	-0.0899	-0.0084	-0.1257
$MarketType$	-0.0235	-0.7477	-0.0233	-0.7464	-0.0216	-0.6892
$Sentiment$	0.0096	0.3004	0.0070	0.2191	0.0070	0.2194
$News$	-0.0012	-0.0547	0.0055	0.2533	0.0073	0.3340
$NumberMessages$	-0.0053	-0.6731	-0.0011	-0.1397	-0.0025	-0.3091
$StockPromoter$	-0.0426**	-2.2075	-0.0383**	-1.9695	-0.0382*	-1.9537
$PumpTracker$	-0.0806***	-2.6390	-0.0803***	-2.6645	-0.0767**	-2.4907
$IRAccount$	0.0315*	1.6708	0.0301	1.6019	0.0301	1.6031
$LinkPct$	0.0198	0.6300			0.0223	0.7117
$RetweetPct$	0.0355	0.7957			0.0334	0.7479
$Marijuana$			-0.0414*	-1.8793	-0.0414*	-1.8759
Adj-R^2 (%)	4.23		4.65		4.48	
Observations	635		635		635	

This table reports the results of the equation $CAR^i_{t+1,t+n} = \alpha + \beta_1 AR^i_t + \beta_2 MarketCap^i_t + \beta_3 Price^i_t + \beta_4 NonTradingDays^i_t + \beta_5 MarketType^i_t + \beta_6 Sentiment^i_t + \beta_7 News^i_t + \beta_8 NumberMessages^i_t + \beta_9 StockPromoter^i_t + \beta_{10} PumpTracker^i_t + \beta_{11} IRAccount^i_t + \beta_{12} LinkPct^i_t + \beta_{13} RetweetPct^i_t + \beta_{14} Cannabis^i_t + \epsilon_t$ for n=5. Standard errors are computed using White (1980) heteroskedasticity robust standard errors. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The regression includes 635 observations.